An Adaptive, Semi-Structured Language Model Approach to Spam Filtering on a New Corpus

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The development of effective spam filters requires realistic experimental corpora.

Recent developments are starting to bring this about – TREC 2005, Enron etc. (Cormack and Lynam, Klimt and Yang . . .)

Two spam filtering datasets are better than one: our contribution – GenSpam.

Build classifiers to take advantage of the specific characteristics of the spam filtering task.
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GenSpam Overview

- 9072 genuine, personal email messages sourced from 15 friends and colleagues of the author.
- 32332 spam email messages sourced from sections 10-29 of the spamarchive collection, along with a batch collected by the author and colleagues.
- Time period: 2002-2003 (genuine mail more widely time-distributed).
Split

Aim is to facilitate experiments with a large background training set and a smaller, specialised set for adaptation.

- **Training set**: 8018 genuine, 31235 spam
- **Adaptation set**: 300 genuine, 300 spam
- **Test set**: 754 genuine, 797 spam

*Adaptation* and *Test* sets sourced from two inboxes during Nov 2002 – June 2003
Relevant information is extracted from the raw email data and marked up in XML.

Retained fields include: *Date*, *From*, *To*, *Subject*, *Content-Type* and *Body*.

Meta-level structure and attachment type preserved but attachment content discarded, except for text and HTML.

Text embedding preserved.
Anonymisation

- Identity protection is clearly an issue for personal email.
- We use a combination of part-of-speech analysis, pattern matching and manual examination to ‘anonymise’ the data.
- Only top-level domain (TLD) information is retained in the From and To fields.
  bwm23@cam.ac.uk → ac.uk
  sam@spamjam.co.uk → co.uk
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Anonymisation

The following labels are used as anonymous markers in free text:

- &NAME (proper name)
- &CHAR (individual character)
- &NUM (number)
- &EMAIL (email address)
- &URL (internet URL)
An example of the format of *GenSpam*:

```xml
<Message>
  <From> net </From>
  <To> ac.uk </To>
  <Subject>
  ^ Re : Hello everybody </Text_Normal>
  </Subject>
  <Date> Tue, 15 Apr 2003 18:40:56 +0100 </Date>
  <Content-Type> text/plain; charset="iso-8859-1" </Content-Type>
  <MessageBody>
  ^ Dear &NAME ,
  ^ I am glad to hear you 're safely back in &NAME .
  ^ All the best
  ^ &NAME
  ^ - On &NUM December &NUM : &NUM &NAME ( &EMAIL ) wrote :
  ...
  </Text_Normal>
  </MessageBody>
</Message>
```
A classification model for semi-structured documents (benchmarking GenSpam)…
Semi-Structured Document Classification

- A document is viewed as a tree.
- Non-leaf nodes represent meta-level structure
- Leaf nodes represent actual content
Basic Decision Rule

\[ \text{Decide}(D_i \rightarrow C_j) \text{ where } j = \arg \max_k [P(C_k|D_i)] \]

- Idea: calculate posterior probabilities of individual document nodes and combine using the tree structure.
- Posterior for entire document is posterior for top-level node.
Non-leaf node posterior is estimated as a weighted interpolation of its subnode posteriors.

\[
P(C_j|D_i) = \sum_{n=1}^{N} \lambda_n [P(C_j^n|D_i^n)]
\]
Leaf Node Estimation

Leaf node posterior estimated in standard generative fashion:

\[
P(C_j^n | D_i^n) = \frac{P(C_j^n) \cdot P(D_i^n | C_j^n)}{P(D_i^n)}
\]

- \(P(C_j^n)\) is the class prior
- \(P(D_i^n)\) is the document prior and constant with respect to class, though important for normalisation.
- It is calculated by \(\sum_{k=1}^{|C|} P(C_k^n) \cdot P(D_i^n | C_k^n)\)
- \(P(D_i^n | C_j^n)\) is the language model probability of the field.
We use $n$-gram language models:

$$
P_N(t_1, \ldots, t_K) = \prod_{i=1}^{K} P(t_i | t_{i-N+1}, \ldots, t_{i-1})
$$

Sparsity handled by Katz back-off:

$$
P(t_j | t_i) = \begin{cases} 
  d(f(t_i, t_j)) \frac{f(t_i, t_j)}{f(t_i)} & \text{if } f(t_i, t_j) > C \\
  \alpha(t_i) P(t_j) & \text{otherwise}
\end{cases}
$$

where $f$ is the frequency-count function
$d$ is the discounting function
$\alpha$ is the back-off weight
$C$ is the $n$-gram cutoff point
We use a simple discounting function – *confidence discounting*:

\[
d(r) = \frac{r}{R} \omega
\]

where \( R \) is the number of distinct \( n \)-gram frequencies. 
\( \omega \) represents a ceiling on discount mass (\( \sim 1 \)).

Idea: confidence in an \( n \)-gram estimate is based on the absolute frequency of that \( n \)-gram in the training data. Higher confidence results in less discounted probability mass.
Unseen Event Modelling

A small probability must be assigned to events that remain unobserved at the end of the back-off chain. We can use this to model discrepancies between the likelihood of observing previously unseen events in spam/genuine mail.
Adaptivity

Spam filters need to be *adaptive*.

Two forms of adaptivity:

- Adapt to changes in the nature of email over time.
- Fit individual user instances while taking account of evidence of accumulated common knowledge (client-server analogy).

One potential solution is to employ two sets of language models:

- a larger, static background set.
- a smaller, user-specific set to be regularly re-trained with new evidence.

Evidence from both these sets of models would then be combined.
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One potential solution is to employ two sets of language models:
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Adaptive Decision Rule

\[ \text{Decide}(D_i \rightarrow C_j) \ldots \ j = \arg \max_k [\lambda_s P_s(C_k|D_i) + \lambda_d P_d(C_k|D_i)] \]
For benchmarking the *GenSpam* corpus we use:

- Multinomial Naïve Bayes (MNB)
- Support Vector Machines (SVM) – Vapnik 95, Joachims 98
- Bayesian Logistic Regression (BLR) – Genkin et. al 05
- Interpolated Language Model (ILM) – our classifier

SVM and BLR both state-of-the-art on text categorization.
Hyperparameter Tuning

ILM:
- Interpolation weights
- Unseen event estimates
- $n$-gram cutoff (for higher-order $n$-grams)

SVM:
- Kernel type (linear)
- Regularization parameter

BLR:
- Prior distribution type (Gaussian)
- Prior variance
Asymmetric Classification

- Spam filtering requires near-perfect recall of genuine mail.
- Evaluate classifiers under genuine recall threshold constraint: recall $\geq 0.995$ (\(\leq 1\) in 200 genuine messages missed)
- MNB, SVM, BLR – bias decision boundary
- ILM – bias language models through unseen estimate modification
## Results

<table>
<thead>
<tr>
<th>Training Data</th>
<th>Classifier</th>
<th>GEN recall</th>
<th>SPAM recall</th>
<th>accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Training</strong></td>
<td>MNB</td>
<td>0.9960</td>
<td>0.1556</td>
<td>0.5642</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.9960</td>
<td>0.7064</td>
<td>0.8472</td>
</tr>
<tr>
<td></td>
<td>BLR</td>
<td>0.9960</td>
<td>0.8105</td>
<td>0.9007</td>
</tr>
<tr>
<td></td>
<td>ILM Unigram</td>
<td>0.9960</td>
<td>0.7340</td>
<td>0.8614</td>
</tr>
<tr>
<td></td>
<td>ILM Bigram</td>
<td>0.9960</td>
<td>0.8331</td>
<td><strong>0.9123</strong></td>
</tr>
<tr>
<td><strong>Adaptation</strong></td>
<td>MNB</td>
<td>0.9960</td>
<td>0.4090</td>
<td>0.6944</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.9960</td>
<td>0.9147</td>
<td>0.9491</td>
</tr>
<tr>
<td></td>
<td>BLR</td>
<td>0.9960</td>
<td>0.9097</td>
<td><strong>0.9542</strong></td>
</tr>
<tr>
<td></td>
<td>ILM Unigram</td>
<td>0.9960</td>
<td>0.8269</td>
<td>0.9091</td>
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<tr>
<td></td>
<td>ILM Bigram</td>
<td>0.9960</td>
<td>0.8934</td>
<td>0.9433</td>
</tr>
<tr>
<td><strong>Combined</strong></td>
<td>MNB</td>
<td>0.9960</td>
<td>0.4103</td>
<td>0.6950</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.9960</td>
<td>0.8808</td>
<td>0.9368</td>
</tr>
<tr>
<td></td>
<td>BLR</td>
<td>0.9960</td>
<td>0.9021</td>
<td>0.9478</td>
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<tr>
<td></td>
<td>ILM Unigram</td>
<td>0.9960</td>
<td>0.9573</td>
<td>0.9761</td>
</tr>
<tr>
<td></td>
<td>ILM Bigram</td>
<td>0.9960</td>
<td>0.9674</td>
<td><strong>0.9813</strong></td>
</tr>
</tbody>
</table>

**Table:** Asymmetric results (best results for each dataset in bold)
ROC Curves

![ROC Curves Graph]

- GEN recall
- SPAM recall
- SVM
- BBR
- ILM (unigram)
- ILM (bigram)

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LM Approach to Spam Filtering on a New Corpus
Discussion

ILM Advantages:
- Efficient linear ML training of $n$-gram LMs.
- Efficient combination of distinct distributional evidence.
- Native probabilistic output.
- Effective bias control.

ILM Disadvantages:
- Potentially expensive hyperparameter estimation.
- Sensitivity to domain character adaptation – a relevant issue for spam filtering.
Conclusions:

- Spam filtering research needs realistic corpora – *GenSpam*
- ILM classification model has some useful properties for spam filtering.

Future work:

- Update spam component of *GenSpam*.
- Hyperparameter estimation techniques for ILM.
- Discriminative techniques for semi-structured spam filtering.
- Combine separate distributional evidence in SVM, BLR etc.